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Abstract

We examine whether global or local events are important drivers in causing major shifts and excessive volatility in Islamic indexes than in conventional indexes. We apply an iterative cumulative sum of squares (ICSS) algorithm to identify structural breaks in the volatility of several major Dow Jones Islamic and conventional indexes over the period 1996-2009. The results show that both indexes have been affected by variance changes. The null hypothesis of equality of variance between both indexes is not rejected for the majority of sub-periods defined from ICSS. When the null hypothesis is rejected, the Islamic indexes exhibit slightly highest volatilities.

Keywords: Islamic finance; Volatility; Sudden changes; Islamic indexes; Conventional indexes.

JEL Classification: G01, G21, G28.

1 Introduction

There has been large-scale growth in Islamic finance and banking in Muslim countries and around the world during the last twenty years. This growth is influenced by factors including the introduction of broad macroeconomic and structural reforms in financial systems, the liberalization of capital movements, privatization, the global integration of financial markets, and the introduction of innovative and new Islamic products (Zaher and Hassan, 2001). Nevertheless, Islamic finance has entered a bright new stage of development, emerging after the global financial crisis as a more equitable and efficient alternative to the Western approach.

Islamic finance, as is well known, is based on the application of classical Islamic law in the management of money: this implies the prohibition of interest, of excessive risk, of gambling, the exclusion of investments in arms, alcohol, casinos, tobacco, pornography and pork, and a major attention on social welfare. Like any other modern avatars of ethical investments[1], such as *green*, *faith* or *socially responsible* investments, the Islamic investing aims at generating low volatility returns and value enhancement opportunities by focusing on low-debt, non-financial, social-ethical investment vehicles (De Lorenzo, 2001). [2]

Most defenders of ethical and Islamic investing point out that the underlying screening process implies that the eligible selected firms have stronger and much stable financial positions and are more successful than the excluded firms. On the other hand, because of monitoring and screening costs or potentially reduced levels of diversification inherent to the screening process, unscreened firms may outperform ethical or Islamic investment vehicles. Moreover, as noted by Hussein and Omran (2005), the screening process tends to systematically exclude large firms from the global universe of investable equities, which implies that the remaining eligible firms are smaller and exhibit more volatile returns.

Langbein and Posner (1980) are the first to argue that ethical investments may involve higher risk than their conventional counterparts. However, by comparing the returns of a well-established index of socially responsible firms (Domini Social Index, DSI)

[1] Cowton (1994) defines ethical investment as the use of ethical and social criteria in the selection and management of investment portfolios, generally consisting of company shares. Ethical investors are not only concerned about the financial returns on their portfolios and the risks involved but also with the characteristics of the companies in which the funds are placed.

[2] The most important difference between Islamic and other ethical funds is that in addition to the exclusion of particular sectors, Islamic funds do not deal in fixed income market and the receipt and payment of interest is not permitted (Hussein, 2004).

to other conventional market portfolios (such as S&P 500 or CRSP value-weighted market index), Sauer (1997) fails to find that ethical screening implies higher volatility of returns and reduced financial performance. In the same vein, Statman (2000) finds that the risk-adjusted returns of S&P 500 over the 1990–1998 period do not differ significantly from those of the DSI, although the ethical index exhibits a slightly higher volatility than its conventional counterpart.

Despite the increasing importance and popularity of performance of ethical investments over the past several years, the existing literature on Islamic investing contains only a few empirical studies.

Hakim and Rashidan (2002) find that the Islamic index is influenced by other factors than the broad market movements in stock prices and interest rates from a cointegration analysis. More importantly, their findings suggest that the Islamic index exhibits unique risk-returns characteristics and the screening process applied to exclude Shari'ah-non-compliant firms does not adversely affect the performance of the Islamic index.

Yusof and Majid (2007) examine the extent to which the conditional volatilities of both Islamic and conventional indexes in Malaysia are affected by monetary policy variables. The most important finding is that the interest rate volatility affects the conventional, but not the Islamic, stock market volatility, which is quite intuitive.

Ahmad and Ibrahim (2002), Hussein (2004, 2005), Hussein and Omran (2005), Girard and Hassan (2006) and Dharani and Natarajan (2011a) investigate the impact of ethical screening on the performance of Islamic indexes relative to their conventional counterparts. All these studies indicate that there is no significant difference in performance of both indexes over the entire period. Nevertheless, Islamic indexes display significant positive abnormal returns observed in the bull market period and underperform the counterpart index in the bear market.

Moreover, the study of Dharani and Natarajan (2011b) indicates that the seasonal variation exits very much in Shariah index implying the existence of abnormal returns.

Rahman and Wajdi (2006) show that the Shariah-compliant firms pay higher dividend to their shareholders than non-Shariah-compliant firms. Further, this study finds that Shariah-compliant firms facing less agency cost than Shariah-compliant firms.

Albaity and Ahmad (2008) find that Islamic and conventional Malaysian stock market indexes over the 1999–2005 period move in tandem in the short-, as well as in the long-run. Nevertheless, no long run relationship between Islamic and non-Islamic indexes is found by Biek and Wardhana (2009).

According to Sadegi (2008) the introduction of the Shariah index has positive and strong impact on the financial performance of the Shariah compliant stock.
The main findings of Seng et al. (2009) are that Shariah-compliant indexes offer an opportunity for portfolio diversification with mainstream indexes and other ethical funds within the UK.

The present paper contributes to the literature on the impact of the *Shari'ah* filtering criteria on the volatility of Dow Jones Islamic indexes relative to their conventional counterparts. Understanding the behavior of volatility in Islamic and conventional indexes is important to risk management, derivative pricing and hedging, market making, market timing, portfolio selection, and many other financial activities. Contrary to the previous studies that only focused on long and medium-term bull and bear markets, in this study we examine whether global or local events are more important in causing (i) major shifts and (ii) more volatility in Islamic indexes than in non-Islamic indexes. Financial market participants can benefit from a better understanding of how shocks can affect volatility over time, especially whether the shocks are persistent or short lived.

To address our main research question, we use an appropriate methodology to identify breakpoints and sudden shifts in volatility. A relatively recent approach to test for volatility shifts is the iterative cumulative sums of squares (ICSS) algorithm (Inclan and Tiao, 1994; Sansó et al., 2004). This algorithm allows for detecting multiple breakpoints in variance and has been extensively used for identifying changes in the volatility of financial time series (Hammoumdeh and Li, 2008; Kasman, 2009; and Wang and Moore, 2009, among others). Nevertheless, Rodrigues and Rubia (2011) show that the asymptotic distribution of the ICSS test statistics varies under additive outliers, which are usually present in financial time series (e.g., Charles and Darné, 2005; Bali and Guirguis, 2007). The critical values from this distribution generally are inadequate for the test, which finds too many breaks. Therefore, we first employ the method of Franses and Ghijsels (1999) to detect and correct for additive outliers in stock market returns from Generalized AutoRegressive Conditional Heteroskedasticty (GARCH) models. We also examine whether these outliers tend to be social, political or economic. Using the outlier-corrected return series, we then apply the ICSS algorithm to detect sudden changes in volatility.
The results show that both Islamic and conventional indexes have been affected by variance changes. We then test the null hypothesis of equality of variance between Islamic and conventional indexes over various sub-periods defined with respect to the

identified sudden changes in variance. The statistical tests confirm the null hypothesis over the vast majority of sub-periods. However, when the variance is not the same across the two types of indexes, the Islamic indexes exhibit higher volatilities (as measured by the standard deviation) than their conventional counterparts.

This article is organized as follows. Section 2 describes the sequential procedure for detecting outliers in stock market indexes returns, and the modified ICSS algorithm used to identify sudden variance breaks in Islamic and conventional indexes. The empirical results are discussed in Section 3. Finally, Section 4 concludes.

2 Methodology

2.1 Sudden change detection

The most popular statistical methods specifically designed to detect breaks in volatility are CUSUM-type tests. As underlined by Rodrigues and Rubia (2011), the ability of the CUSUM tests to identify structural changes depends of the underlying assumptions. Financial data display a time varying volatility patterns, well known as volatility clustering. Andreou and Ghysels (2002) illustrate the pervasive effect persistent volatility on CUSUM-type tests experimentally. Their results indicate that the Kokoszka and Leipus (2000) test has a good properties in presence of conditional heteroscedasticity. Sansó et al. (2004) propose a more general test that one of Kokoszka and Leipus (2000) based on the iterative cumulative sum of squares (ICSS) algorithm developed by Inclán and Tiao (1994).

Let $e_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ is the price of the index i at the time t, so that e_t is the percent return of the index i from period $t-1$ to t. $\{e_t\}$ is then assumed to be a series of independent observations from a normal distribution with zero mean and unconditional variance σ_t^2 for $t = 1, \ldots, T$. Assume that the variance within each interval is denoted by σ_j^2, $j = 0, 1, \ldots, N_T$, where N_T is the total number of variance changes and $1 < \kappa_1 < \kappa_2 < \cdots < \kappa_{N_T} < T$ are the set of breakpoints. Then the variances over the N_T intervals are defined as

$$
\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < \kappa_1 \\ \sigma_1^2, & \kappa_1 < t < \kappa_2 \\ \dots & \\ \sigma_{N_T}^2, & \kappa_{N_T} < t < T \end{cases}
$$

The cumulative sum of squares is used to estimate the number of variance changes and to detect the point in time of each variance shift. The cumulative sum of the squared observations from the beginning of the series to the kth point in time is expressed as $C_k = \sum_{t=1}^{k} e_t^2$ for $k = 1, \dots, T$. In order to test the null hypothesis of constant unconditional variance, the Inclán–Tiao statistic is given by:

$$
IT = \sup_k |(T/2)^{0.5} D_k| \tag{1}
$$

where $D_k = \left(\frac{C_k}{C_T}\right) - \left(\frac{k}{T}\right)$, with C_T is the sum of the squared residuals from the whole sample period. The value of k that maximizes $|(T/2)^{0.5} D_k|$ is the estimate of the break date. The ICSS algorithm systematically looks for breakpoints along the sample. If there are no variance shifts over the whole sample period, D_k will oscillate around zero. Otherwise, if there are one or more variance shifts, D_k will departure from zero. The asymptotic distribution of IT is given by $sup_r |W^*(r)|$, where $W^*(r) = W(r) - rW(1)$ is a Brownian bridge and $W(r)$ is standard Brownian motion. Finite-sample critical values can be generated by simulation.

The IT statistic is designed for i.i.d. processes, which is a very strong assumption for financial data, in which there is evidence of conditional heteroskedasticity. Sansó et al. (2004) showed that the size distortions are important for heteroskedastic conditional variance processes from Monte carlo simulations. Their results thus invalidate in practice the use of this test for financial time series. To overcome this problem, Sansó et al. (2004) proposed a new test that explicitly consider the fourth moment properties of the disturbances and the conditional heteroskedasticity.[3] They suggested a non-parametric adjustment to the IT statistic that allows e_t to obey a wide class of dependent processes under the null hypothesis. As suggested by Sansó et al. (2004), we use a non-parametric adjustment based on the Bartlett kernel, and the adjusted statistic[4] is

[3] Bacmann and Dubois (2002) show that one way to circumvent this problem is by filtering the return series by a GARCH (1,1) model, and applying the ICSS algorithm developed by Inclán and Tiao (1994) to the standardized residuals obtained from the estimation. Fernandez (2006) propose an alternative approach to testing for variance homogeneity based on wavelet analysis.

[4] This adjusted statistic is equivalent to the non-parametric test proposed by Kokoszka and Leipus (2000).

given by:

$$AIT = \sup_k |T^{-0.5} G_k| \tag{2}$$

where $G_k = \hat{\lambda}^{-0.5}\left[C_k - \left(\frac{k}{T}\right)C_T\right]$, $\hat{\lambda} = \hat{\gamma}_0 + 2\sum_{l=1}^{m}\left[1 - l(m+1)^{-1}\right]\hat{\gamma}_l$, $\hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(e_t^2 - \hat{\sigma}^2)(e_{t-l}^2 - \hat{\sigma}^2)$, $\hat{\sigma}^2 = T^{-1}C_T$, and the lag truncation parameter m is selected using the procedure in Newey and West (1994). Under general conditions, the asymptotic distribution of AIT is also given by $sup_r|W^*(r)|$, and finite-sample critical values can be generated by simulation.

2.2 Outlier detection in GARCH models

Several studies have showed that financial data may be affected by contaminated observations (Balke and Fomby, 1994 ; Charles and Darné, 2005). This type of observations, called outliers, are aberrant observations that are away from the rest of the data. In financial markets, outliers are linked to rare shocks not related to the trading process, or abnormal flows of information arrivals. Rodrigues and Rubia (2011) discuss the effects that sample contamination has on the asymptotic properties of CUSUM-type tests for detecting change points in variance and characterize the finite sample behavior by means of Monte Carlo simulations. They focus on additive outliers, that is exogenous changes that directly affect the series, which prove able to generate large size distortions in these tests. The authors show that the Sansó et al. (2004) test exhibits low power and tends to find few or no breaks at all.

As suggested by Rodrigues and Rubia (2011), we first detect outliers in the stock market indexes before we attempt to identify the variance changes.[5] There are several methods for detecting outliers (e.g., Sakata and White, 1998; Hotta and Tsay, 1999; Doornik and Ooms, 2009). Here we use the method proposed by Franses and Ghijsels (1999), which extended the outlier detection procedure in ARMA (linear) models developed by Chen and Liu (1993) to GARCH models.

Consider the returns series ε_t, which is defined by $\varepsilon_t = \log P_t - \log P_{t-1}$, where P_t is the observed price at time t, and consider the GARCH(1,1) model

$$\varepsilon_t = z_t\sqrt{h_t}, \tag{3}$$

$$\varepsilon_t \sim N(0, \sqrt{h_t}), \qquad z_t \sim i.i.d.N(0,1),$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{4}$$

[5] Further, Inclán and Tiao (1994) advised that "*it is advisable to complement the search for variance changes with a procedure for outlier detection*".

where $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$, such that the model is covariance-stationary. The GARCH(1,1) model can be rewritten as an ARMA(1,1) model for ε_t^2 (see Bollerslev, 1986)

$$\varepsilon_t^2 = \alpha_0 + (\alpha_1 + \beta_1)\varepsilon_{t-1}^2 + \nu_t - \beta_1 \nu_{t-1} \tag{5}$$

where $\nu_t = \varepsilon_t^2 - h_t$. The additive outliers (AO) can be modelled by regression polynomials as follows:

$$e_t^2 = \varepsilon_t^2 + \omega\xi(B)I_t(\tau) \tag{6}$$

where ε_t is a GARCH(1,1) process, $\xi(B) = 1$ is the polynomial characterizing the AO occurring at time $t = \tau$, ω represents its impact on the series and $I_t(\tau)$ is an indicator function with the value of 1 at time $t = \tau$ and 0 otherwise.

A GARCH(1,1) model is fitted to ε_t in (3) and the residuals are obtained:

$$\eta_t = \frac{-\alpha_0}{1 - \beta_1 B} + \pi(B)e_t^2 = \nu_t + \pi(B)\xi(B)\omega I_t(\tau) \tag{7}$$

where $\pi(B) = \big(1 - (\alpha_1 + \beta_1)B\big)(1 - \beta_1 B)^{-1}$. The expression (7) can be interpreted as a regression model for η_t, i.e.

$$\eta_t = \omega x_t + \nu_t \tag{8}$$

with $x_t = 0$ for $t < \tau$, $x_t = 1$ for $t = \tau$, and $x_{\tau+k} = -\pi_k$ (for $t > \tau$ and $k > 0$. The detection of the outliers is based on likelihood ratio statistics, given by:

$$\hat{\tau} = \big(\hat{\omega}(\tau)/\hat{\sigma}_\nu\big)\Big(\sum_{t=\tau}^{n} x_t^2\Big)^{1/2} \qquad \text{with } \hat{\omega}(\tau) = \Big(\sum_{t=\tau}^{n} x_t \eta_t\Big)\Big(\sum_{t=\tau}^{n} x_t^2\Big)^{-1}$$

where $\hat{\omega}(\tau)$ denotes the estimation of the outlier impact at time $t = \tau$, and $\hat{\sigma}_\nu^2$ is the estimated variance of the residual process.

Outliers are identified through running a sequential detection procedure, consisting of an outer and an inner iteration. In the outer iteration, assuming that there are no outliers, a GARCH(1,1) model is estimated, obtaining the residuals. The results from the outer iteration are then used in the inner iteration to identify outliers. The likelihood ratio test statistics are calculated for each observations. The largest absolute value of these test statistics $\hat{\tau}_{max} = \max_{1 \leq \tau \leq n} |\hat{\tau}|$ is compared to a pre-specified critical value (based on simulation experiments), and if the test statistic is larger, an outlier is found at time $t = \tau$. When an outlier is detected, the effect of the outlier is removed from the data as follows: the observation e_t is adjusted at time $t = \tau$ to obtain the corrected ε_t^* via (6) using the $\hat{\omega}$, i.e. $\varepsilon_t^* = e_t - \hat{\omega}\xi I_t(\tau)$. This process is repeated until no more outliers can be found. Next, return to the outer iteration in which the GARCH model is re-estimated, using the corrected data, and start the inner iteration again. This procedure is repeated until no outlier is found.

3 Empirical implementation and results

3.1 Description of the data

In February 1999, New York-based Dow Jones was the first to launch Shari'ah-compliant indexes - i.e. based on a subset of investable equities that are compatible with the Islamic finance principles - in response to the increasing demand for ethical investments from the Muslim community and other socially responsible investors. London-based FTSE, as well as Standard and Poor's, also launched their specialized Islamic market indexes in 1999, and several years afterwards, respectively. Broadly speaking, Islamic indexes track the performance of a subset of eligible stocks that are already included in the corresponding global indexes. To become eligible for inclusion in the Islamic index, a company has to satisfy two main screening criteria (see Standard & Poor's, 2007; Dow Jones, 2009):

- The *industry* screen, which attempts to remove any companies having primary business activities that are not compatible with the principles of Islamic finance (e.g. alcohol; pork-related products; conventional financial services; entertainment; tobacco; weapons and defense);
- The *financial ratios* screen, which is intended to remove companies based on their levels of leverage or interest income; all of the following financial ratios must not exceed 33% in order for a company to be included in the index: (i) the debt ratio; (ii) the ratio of interest income to total revenue; (iii) the ratio of accounts receivables to the market value of total assets.

In addition, the composition of the indexes is reviewed on a quarterly basis, as well as on an ongoing basis to take into account extraordinary events, such us delisting activities; bankruptcies; M&As. All revisions are supervised by an independent Shari'ah board composed of Islamic scholars.

For the purpose of our analysis, we consider several major (conventional and Islamic) daily stock market indexes spanning January 1^{st}, 1996 to December 31^{st}, 2009 (3,653 observations): Dow Jones (Islamic) Asian, Dow Jones (Islamic) Canada, Dow Jones (Islamic) Emergent, Dow Jones (Islamic) Japan, Dow Jones (Islamic) United Kingdom, Dow Jones (Islamic) United States, Dow Jones (Islamic) World. The daily returns are computed as the natural logarithmic first difference of the daily closing prices, which are obtained from the Dow Jones company database. The logarithmic stock returns are multiplied by 100 to avoid convergence problems.

Table 1 gives the number of stocks used in the calculation of each index, as well as basic descriptive statistics for the return series. The number of constituents included in the conventional indexes varies from 261 (the DJ UK index) to 6,571 firms (the DJ World index). The application of the filtering criteria reduces the number of stocks included in the Islamic indexes by 60-70% (compared with the broad universe of investable stocks included in the conventional indexes). The Islamic market indexes display higher mean returns than the conventional market indexes but they are also slightly more volatile. All the returns are highly non-normal, i.e. showing evidence of negative excess skewness and excess kurtosis. All series are leptokurtic (i.e., fat-tailed distribution) and thus the variance of the index prices is principally due to infrequent but extreme deviations. The Lagrange Multiplier test for the presence of the ARCH effect indicates clearly that the prices show strong conditional heteroscedasticity, which is a common feature of financial data. In other words, there are quiet periods with small price changes and turbulent periods with large oscillations.

3.2 Outliers in daily stock market index returns

Tables 2–4 give the identified outliers for all the indexes in chronological order. In addition, we also associate the date corresponding to each outlier to a specific (economic, political or financial) event that occurred near that date. As expected, outliers have been detected in all the series, and most of them are due to the 2008 financial crisis. Note that the conventional and Islamic indexes display the same number of outliers, and in the vast majority of cases the corresponding dates are also the same.

Over the entire sample period covering 14 years of daily data (January 1st, 1996 – December 31st, 2009), we are able to match about 70% of all identified outliers with events related to the global financial crisis of 2007. The remaining outliers observed at the beginning of the analyzed period can be explained by various adverse events associated with the 1997 Asian financial crisis, the Russian crisis of summer 1998, as well as other macroeconomic news, such as unanticipated increases in interest rates, consumer price indexes, commodities prices or unemployment rates.[6] According to Charles and Darné (2006), the terrorist attacks in the US on September 11th, 2001, had a large impact on international stock markets. We confirm this finding by showing that

[6] This is consistent with the result reported by Flannery and Protopapadakis (2002), according to which some macroeconomic news announcements have a significant impact on the stock market returns.

most conventional and Islamic indexes experienced large shocks due to the terrorist attacks.[7]

There are an impressive number of events related to the global financial crisis likely to explain the outliers detected in stock market data after 2007. We performed an extensive search on each date reported in Tables 2–4 using Dow Jones Factiva (Dow Jones and Reuters newswires; key newspapers; and other sources) in order to match each of the identified outliers to one (or several) significant event(s) that occurred on (or near) that date. It is beyond the scope of the paper to discuss at length all these events. Rather, in what follows we decided to mention, with the benefit of hindsight, only the most significant events that shaped the evolution of the subprime crisis.

We observe without surprise a clustering of outliers during the global panic of the fall 2008, when Dow Jones indexes experienced dramatic daily swings and attained the highest levels of volatility ever recorded in more than 100 years. For many observers it was the failure of Lehman Brothers on September 15th, 2008 that triggered the panic in financial markets (see, e.g., Acharya, Philippon, Richardson, and Roubini, 2009; Portes, 2008). However, other influential economists embraced the opposite view, arguing that it was not Lehman's failure but the uncertainty surrounding the ill-conceived $2\frac{1}{2}$-page draft of the Troubled Asset Relief Program (TARP) released several days afterward that effectively triggered the global panic of the fall 2008 (see Taylor, 2009; Cochrane and Zingales, 2009).[8] Interestingly, we find no outlier in stock market data related to the collapse of Lehman Brothers but we do find outliers that may be undoubtedly associated with the announcement of TARP on September 19th and the rejection of Paulson's bailout plan by the House of Representatives on September 29th. This finding tends to lend empirical support to Taylor (2009) and Cochrane and Zingales's (2009) thesis according to which the systemic event during the fall of 2008 was the ill-conceived regulatory response rather than the failure of one of the largest financial institutions in the US.

In fact, a large number of outliers can be explained by the government actions in response to the crisis: public announcements of revisions to bailout plans; bank rescue packages adopted in other countries then the US (the Netherlands, UK, Swiss, Japan, continental Europe); recapitalization plans for large European banks; bailout

[7] The US markets canceled trading for a week after the terrorist attacks and the Federal Reserve undertook actions to avoid a stock market crash and calm down investors.

[8] Basically, these authors show that some risk indicators of stress in the financial sector reacted apathetically to Lehman's collapse, while the same stress indicators exhibited very strong and negative responses just after the Federal Reserve Board Chairman Ben Bernanke and Treasury Secretary Henry Paulson testified at the Senate Banking Committee about the TARP, several days later.

plans and temporary guarantee programs for other failing industries (e.g., the US automakers, money market mutual funds); international summits and meetings (e.g., G20 in London; G7 in Washington); temporary bans of short-selling stocks of specific financial institutions; significant interest rate cuts by major central banks. Another explanatory factor that sent tremors through international financial markets during the subprime crisis was the release of bad economic statistics and macroeconomic news. Real estate fears (e.g., the announcement on January 24th, 2008 of the largest single-year drop in US home sales in 25 years), job cuts worse than expected, fears of recession, large drops in the consumer confidence, housing prices and GDP, official declarations of recessions in various countries are representative examples of such bad macroeconomic news.

3.3 Volatility breaks and comparisons of variance estimates

The time periods of a shift in volatility as detected by the modified ICSS algorithm are given in Table 5. The ICSS algorithm identifies variance breaks in all conventional and Islamic indexes, ranging from two to six shifts. The conventional and Islamic indexes displayed the same number of variance changes with the same dates, except for the Emergent indexes for which the dates are slightly different. For example, three sudden changes have been detected both in the DJ Asia and DJ Islamic Asia series, with the following dates: 11/27/1996, 10/23/2002 and 07/26/2007. This result tends to confirm that the Islamic indexes have not been more or less affected by variance changes than the conventional indexes.

As noted by Malik and Hassan (2004), some major events correlate with the regime shifts as identified by the ICSS algorithm, and some events are often marked by the peaks and lows of the market. We believe that these events are contributing factors. However, markets may very well anticipate some events in advance and sometimes respond with a time lag, so we do not expect these events to correlate to changes in sudden variance on any specific day. In this paper, we only suggest that these events may be a contributing factor in the sudden change and make no attempt to show definitely the causes of the sudden changes.

We further perform the Brown-Forsythe test (Brown and Forsythe, 1974) to see whether the constancy of the variances for the various indexes on the sub-periods can be rejected. We use the Brown-Forsythe test to determine whether k samples have equal variance because it is more robust to departures from normality, an assumption that is strongly rejected in our data.[9] The results are reported in Tables 6 and 7. On the whole, the hypothesis of equality of variance between Islamic and conventional indexes over various sub-periods defined with respect to the identified sudden changes in volatility patterns is rejected in all cases for the Canadian indexes and in some few cases for other regional and global indexes. Interestingly, for all DJ indexes there is at least one sub-period over which the null hypothesis is rejected, namely the variance is not the same across conventional and Islamic indexes. In this later case, the Islamic indexes display higher volatility (as measured by the standard deviations) than their conventional counterparts. For example, the DJ Asia index exhibits a standard deviation of 1.29 over the 11/28/1996–10/23/2002 period, whereas that of the DJ Islamic Asia index is of 1.41. This suggests that when the variance is not the same across the two types of indexes, the Islamic index is more risky (in terms of the standard deviation of returns) than the conventional index.[10]

4 Conclusion

The present paper contributes to the literature on the impact of the *Shari'ah* filtering criteria on the volatility of Dow Jones Islamic indexes relative to their conventional counterparts. Contrary to the previous studies that only focused on long and medium-term bull and bear markets, in this study we examine whether global or local events are more important in causing (i) major shifts and (ii) more volatility in Islamic indexes than in non-Islamic indexes.

We first detected the presence of outliers in major Dow Jones Islamic and conventional indexes over the period from January 1996 through December 2009 and

[9]There are numerous tests for equal variances, but, as by Box (1953) points out, many of them are sensitive to departures from normality, outliers and heteroskedasticity. Several tests have been proposed to deal with this problem. Conover et al. (1981) list and compare 60 methods for testing the homogeneity of variance assumption and show that the Brown-Forsythe procedure outperforms all the other procedures. Moreover, Brown and Forsythe (1974) perform Monte Carlo simulations and conclude that using the trimmed mean performs best when the underlying data follows a heavy-tailed distribution and the median performs best when the underlying data follows a skewed distribution.

[10]Some alternative plausible explanations have been proposed in the literature: (i) the existence of some deficiencies in the application of the filtering criteria based on accounting ratios (e.g., some firms that manipulate their financial reports for various raisons may be included among the constituents of the Islamic index while they should not); (ii) the relative under-diversification of the Islamic indexes due to filtering criteria that remove a large number of *Shari'ah* non-compliant firms; and (iii) the systematic exclusion of the largest firms from the broad universe of investable equities included in Islamic indexes due to the financial ratios screen, which implies that the remaining *Shari'ah* compliant firms are smaller and more exposed to volatility shocks. These explanations will be the subject of further research.

then we applied the iterative cumulative sum of squares (ICSS) algorithm to identify sudden changes in volatility. The results showed that both Islamic and conventional indexes have been affected by variance changes.

We then tested the null hypothesis of equality of variance between Islamic and conventional indexes over various sub-periods defined with respect to the identified sudden changes in variance. The statistical tests confirmed the null hypothesis over the vast majority of sub-periods. However, when the variance was not the same across the two types of indexes, the Islamic indexes exhibited slightly higher volatilities than their conventional counterparts.

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References

[1] Albaity M. and Ahmad R., 2008. Performance of Shariah and composite indices: Evidence from Bursa Malaysia. *Journal of Accounting and Finance*, 4, 23-43.

[2] Ahmad Z. and Ibrahim H., 2002. A Study of Performance of the KLSE Shariah Index, *Malaysian Management Journal*, 6, 25-34.

[3] Andreou E. and Ghysels E., 2002. Detecting multiple breaks in financial market volatility dynamics. *Journal of Applied Econometrics*, 17, 579-600.

[4] Bacmann J.F. and Dubois M., 2002. Volatility in emerging stock markets revisited. European Financial Management Association, London Meeting, 26-29 June 2002.

[5] Bali R. and Guirguis H., 2007. Extreme observations and non-normality in ARCH and GARCH. *International Review of Economics and Finance*, 16, 332-346.

[6] Balke N.S. and Fomby T.B., 1994. Large shocks, small shocks, and economic flucutuations: Outliers in macroeconomic time series. *Journal of Applied Econometrics*, 9, 181-200.

[7] Box G.E.P., 1953. Non-normality and tests of variances. *Biometrika*, 40, 318-335.

[8] Brown M.B. and Forsythe A.B., 1974. Robust tests for equality of variances. *Journal of the American Statistical Association*, 69, 364-367.

[9] Charles A. and Darné O., 2005. Outliers and GARCH models in financial data. *Economics Letters*, 86, 347-352.

[10] Charles A. and Darné O., 2006. Large shocks and the september 11th terrorist attacks on international stocks markets. *Economic Modelling*, 23, 683-698.

[11] Chen C. and Liu L.M., 1993. Joint estimation of model parameters and outlier effects in time series. *Journal of the American Statistical Association*, 88, 284-297.

[12] Conover W.J, Johnson M.E. and Johnson, M.M., 1981. A comparative study of tests for homogeneity of variances, with applications to the outer continental shelf bidding data. *Technometrics*, 23, 351-361.

[13] Cowton, C.J. 1994. The Development of Ethical Investment Products, in A.R. Pindl and B. Brodhan (eds), *Ethical Conflicts in Finance*, Oxford: Blackwell.

[14] De Lorenzo Y.T., 2001. Shariah supervision of islamic mutual funds, paper in *Proceedings of Fifth Harvard University Forum on Islamic Finance*, Harvard University.

[15] Dharani M. and Natarajan P., 2011a. Equanimity of risk and return relationship between shariah index and general index in India. *Journal of Economics and Behavioral Studies*, 2, 213-222.

[16] Dharani M. and Natarajan P., 2011b. Seasonal Anomalies between S&P CNX Nifty Shariah Index and S&P CNX Nifty Index in India. *Journal of Social and Development Sciences*, 1, 101-108.

[17] Doornik J.A. and Ooms M., 2002. Outlier detection in GARCH models. Working paper, Nuffield College, University of Oxford.

[18] Dow Jones, 2009. Guide to the Dow Jones Islamic Market Indexes^{SM}.

[19] Engle R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50, 987-1007.

[20] Fernandez V., 2006. The impact of major global events on volatility shifts: Evidence from the Asian crisis and 9/11. *Economic Systems*, 30, 79-97.

[21] Franses P.H. and Ghijsels H., 1999. Additive outliers, GARCH and forecasting volatility. *International Journal of Forecasting*, 15, 1-9.

[22] Girard E. and Hassan K.M., 2006. Faith-Based Ethical Investing: The Case of Dow Jones Islamic Indexes. Workin paper.

[23] Hakim S. and Rashidian M., 2002. Risk and Return of the Islamic Stock Market. Paper presented at the presentation to Economic Research Forum Annual Meetings, Sharjah, UAE.

[24] Hammoumdeh S. and Li H., 2008. Sudden changes in volatility in emerging markets: The case of Gulf Arab stocks markets. *International Review of Financial Analysis*, 17, 47-63.

[25] Hansen P.R. and Lunde A., 2005. A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics*, 20, 873-889.

[26] Hillebrand E., 2005. Neglecting parameter changes in GARCH models. *Journal of Econometrics*, 129, 121-138.

[27] Hotta L.K. and Tsay R.S., 1999. Outliers in GARCH processes. Manuscript, University of Chicago.

[28] Hussein K., 2004. Ethical investment: Empirical evidence from FTSE Islamic index. *Islamic Economic Studies*, 12, 21-40.

[29] Hussein A.K., 2005. Islamic Investment: Evidence From Dow Jones and FTSE Indices, Working paper, Islamic Business Research Centre, Norway.

[30] Hussein K. and Omran M., 2005. Ethical investment revisited: Evidence from Dow Jones Islamic indexes. *Journal of Investing*, 14, 105-124.

[31] Inclan C. and Tiao G.C., 1994. Use of cumulative sums of squares for retrospective detection of changes of variance. *Journal of the American Statistical Association*, 89, 913-923.

[32] Kasman A., 2009. The impact of sudden changes on the persistence of volatility: Evidence from the BRIC countries. *Applied Economics Letters*, 16, 759-764.

[33] Kokoszka P. and Leipus R., 2000. Change-point estimation in ARCH models. *Bernoulli*, 6, 513-539.

[34] Lamoureux C.G. and Lastrapes W.D., 1990. Persistence in variance, structural change and the GARCH model. *Journal of Business and Economic Statistics*, 8, 225-234.

[35] Langbein J. and Posner R., 1980. Social investing and the law of trusts. *Michigan Law Review*, 97, 72-111.

[36] Malik F. and Hassan S.A., 2004. Modeling volatility in sector index returns with GARCH models using an iterated algorithm. *Journal of Economics and Finance*, 28, 211-225.

[37] Mikosch T. and Stãricã C., 2004. Nonstationarities in financial time series, the long-range dependence, and the IGARCH effects. *Review of Economics and Statistics*, 86, 378-390.

[38] Poon S.H. and Granger C.W., 2003. Forecasting volatility in financial markets: A review. *Journal of Economic Literature*, 16, 478-539.

[39] Rahman F.A. and Wajdi F.M., 2006. Dividend Signaling Hypothesis and Agency Cost: An Investigation on Shariah and Non Shariah Compliant Firms in Kuala Lumpur. *Shariah Index Empirika*, 19, 1-9.

[40] Rapach D.E. and Strauss J.K., 2008. Structural breaks and GARCH models of exchange rate volatility. *Journal of Applied Econometrics*, 23, 65-90.

[41] Rodrigues P.M.M. and Rubia A., 2011. The effects of additive outliers and measurement errors when testing for structural breaks in variance. Oxford Bulletin of Economics and Statistics, 73, 449-468.

[42] Sadeghi M., 2008. Financial Performance of Shariah-Compliant Investment: Evidence from Malaysian Stock Market. *International Research Journal of Finance and Economics*, 20, 15-26.

[43] Sakata S. and White H., 1998. High breakdown point conditional dispersion estimation with application to S&P 500 daily returns volatility. *Econometrica*, 66, 529-567.

[44] Sansó A., Aragó V. and Carrion-i-Silvestre J. (2004). Testing for changes in the unconditional variance of financial time series. *Revista de Economía Financiera*, 4, 32-53.

[45] Sauer D., 1997. The impact of social-responsibility screens on investment performance: Evidence from the Domini 400 Social Index and Domini Equity Mutual Funds. *Review of Financial Economics*, 6, 137-149.

[46] Seng K., Gianluigi G. and Jason L., 2009. Performance of Shariah-Compliant Indices in London and NY Stock Markets and their potential for diversification. *International Journal of Monetary Economics and Finance*, 2, 398-408.

[47] Standard & Poor's, 2007. S&P Shariah Indices: Index methodology.

[48] Statman M., 2000. Socially responsible mutual funds. *Financial Analysts Journal*, 56, 30-39.

[49] Wang P. and Moore T., 2009. Sudden changes in volatility: The case of five Central European stocks markets. *International Financial Markets, institutions & Money*, 19, 33-46.

[50] Yusof R.M. and Majid M.S.A., 2007. Stock market volatility transmission in Malaysia: Islamic versus conventional stock market. *Islamic Economics*, 20, 17-35.

[51] Zaher T.S. and Hassan M.K., 2001. A comparative literature survey of Islamic finance and banking. *Financial Markets, Institutions & Instruments*, 10, 155-199.

Table 1: Summary statistics

Series	N	Mean	St. dev.	Skewness	Kurtosis	Min.	Max.	LM(10)
DJ Asian	3,367	0.01	1.22	-0.10	4.50*	-5.21	5.12	470.57*
DJI Asian	1,079	0.02	1.28	-0.14	6.69*	-5.96	5.24	463.36*
DJ Canada	279	0.05	1.29	-0.21	5.53*	-6.27	6.01	771.29*
DJI Canada	149	0.06	1.70	-0.16	7.86*	-8.21	8.59	679.77*
DJ World	6,571	0.02	0.94	-0.27	7.46*	-4.59	4.54	833.23*
DJI World	2,370	0.03	1.02	-0.14	7.22*	-4.87	4.74	738.12*
DJ Emergent	2,119	0.02	1.26	-0.37	7.49*	-5.98	6.02	654.34*
DJI Emergent	851	0.02	1.34	-0.27	6.74*	-5.98	5.81	490.69*
DJ Japan	1,053	-0.01	1.43	-0.03	6.25*	-6.44	6.24	396.23*
DJI Japan	234	0.01	1.48	-0.06	6.34*	-6.41	6.18	419.41*
DJ UK	261	0.02	1.22	-0.15	7.34*	-5.47	5.81	749.49*
DJI UK	85	0.01	1.32	-0.11	7.09	-5.97	5.92	654.24*
DJ US	1,318	0.01	1.21	-0.80	7.67*	-5.89	6.02	781.90*
DJI US	585	0.03	1.26	-0.06	6.85*	-5.48	5.55	704.55*

N denotes the number of firms in each index. * means significant at 5% level.

Table 2: Outliers in volatility

Date of outliers	Series	Events
28/10/1997	DJ & DJI Canada, DJ & DJI World, DJ & DJI US	Asian crisis
27/08/1998	DJ & DJI Canada	Asian and Russian crisis; fear of contagion in emerging markets
31/08/1998	DJ & DJI US	Deepening of Asian and Russian crises
07/10/1998	DJ & DJI Asia, DJ & DJI Japan	Announcement of possible bank revival plan in Japan
05/01/2000	DJ & DJI Asia, DJ & DJI Japan, DJ & DJI Canada	Fear of rise in interest rates
14/04/2000	DJ & DJI Canada, DJ & DJI US DJ & DJI World, DJ & DJI Asia	Rise in US consumption prices
25/10/2000	DJ & DJI Canada	Fall of Nortel Networks
03/01/2001	DJ & DJI US	Rise in US interest rates
16/02/2001	DJ & DJI Canada	Rise in US production prices
11/09/2001	DJ & DJI Canada, DJ & DJI UK, DJ & DJI Asia, DJ & DJI Islamic Japan	The September 11th terrorist attacks
17/09/2001	DJ & DJI World, DJ & DJI US	
24/07/2002	DJ & DJI US	Investigations against AOL Time Warner
15/10/2002	DJ & DJI World	Good US firm's results
28/04/2004	DJ & DJI Canada	Dismissal of the CEO of Nortel Networks
10/05/2004	DJ & DJI Asia, DJ & DJI Japan,	Fear of rise in US interest rates

Table 3: Outliers in volatility (continued)

Date of outliers	Series	Events
21/01/2008	DJ & DJI UK,	
	DJ & DJI Asia, DJ & DJI Japan	Growing fears of US recession
24/01/2008	DJ & DJI UK	Real estate fears
19/09/2008	DJ & DJI Canada, DJ & DJI World,	Troubled Assets Relief Plan (TARP)
	DJ & DJI UK	unveiled
29/09/2008	DJ & DJI Canada, DJ & DJI World,	Rejection of Paulson's bailout plan
	DJ & DJI UK, DJ & DJI US,	in the House of Representatives
02/10/2008	DJ & DJI Canada	Financial crisis spreads to other
		developed countries
06/10/2008	DJ & DJI Canada, DJ & DJI World,	Revised US bailout plan adopted
	DJ & DJI UK	
08/10/2008	DJ & DJI Asia, DJ & DJI Japan,	IMF predicts a major global
	DJ & DJI UK	economic downturn; Simultaneous cuts
		of interest rates by major central banks
09/10/2008	DJ & DJI Canada, DJ & DJI US	Heavy losses announced in the US
10/10/2008	DJ & DJI Asia, DJ Canada, DJ Islamic Canada,	Contagion of the crisis in Asia and Europe;
	DJ & DJI World, DJ & DJI Japan,	Japanese company Yamato Life
	DJ & DJI UK	files for bankruptcy
13/10/2008	DJ & DJI World, DJ & DJI UK,	US and European government's
	DJ & DJI US, DJ & DJI Asia,	interventions
	DJ & DJI Canada, DJ & DJI Japan	
15/10/2008	DJ & DJI Canada, DJ & DJI World,	Bad economic statistics;
	DJ & DJI UK, DJ & DJI US,	Fear of an impending recession;
	DJ & DJI Asia, DJ & DJI Japan,	US Capital Purchase Program announced
	DJ & DJI UK	
22/10/2008	DJ & DJI Canada, DJ & DJI World,	Bad firm results;
	DJ & DJI UK, DJ & DJI US,	fear of severe and long recession
24/10/2008	DJ & DJI UK	Gordon Brown admits that the UK
		is in recession

Table 4: Outliers in volatility (continued)

Date of outliers	Series	Events
27/10/2008	DJ & DJI Asia, DJ & DJI Canada, DJ & DJI Japan	Fear of a global recession
28/10/2008	DJ & DJI Canada, DJ & DJI World, DJ & DJI US	Anticipation of rate cuts by major central banks
29/10/2008	DJ & DJI Canada, DJ & DJI UK DJ & DJI Asia, DJ & DJI Japan	Interest rate cuts in the US, Japan, Hong Kong, and Taiwan
04/11/2008	DJ & DJI Canada	Obama elected the 44th President of the US
06/11/2008	DJ & DJI Asia, DJ & DJI World, DJ & DJI UK	Predictions of a deep recession in the UK and Eurozone
13/11/2008	DJ & DJI Canada, DJ & DJI US	Announcement that TARP funds would not be used to buy distressed assets
19/11/2008	DJ & DJI World, DJ & DJI US	Federal bailout plan for US automakers rejected
20/11/2008	DJ & DJI Canada, DJ & DJI World, DJ & DJI US	Bad economic statistics; Fear of deflation
21/11/2008	DJ & DJI Canada	Financial weakness of large US banks
24/11/2008	DJ & DJI Canada, DJ & DJI World, DJ & DJI UK	Bailout plan for Citigroup
01/12/2008	DJ & DJI Canada, DJ & DJI World, DJ & DJI UK, DJ & DJI US	Bad economic statistics
08/12/2008	DJ & DJI UK, DJ & DJI World, DJ & DJI Canada	Fear of severe recession Recession officially declared in Canada
20/01/2009	DJ & DJI World	Obama's economic team reveled
02/03/2009	DJ & DJI Canada, DJ & DJI World, DJ & DJI UK	
10/03/2009	DJ & DJI World, DJ & DJI US	Earnings for Citigroup; Increasing risk of inflation
23/03/2009	DJ & DJI World, DJ & DJI US	Geithner's bailout plan
02/04/2009	DJ & DJI UK	G20-summit in London
22/06/2009	DJ & DJI Canada	Financial regulation plan

Table 5: Sudden changes in volatility

Series	Nb. of change points	Date of change break	Series	Nb. of change points	Date of change break
DJ Asia &	3	11/27/1996	DJ Canada &	3	07/30/1998
DJI Asia		10/23/2002	DJI Canada		04/23/2001
		07/26/2007			10/24/2007
DJ Emergent	3	01/16/1997	DJI Emergent	4	05/05/1997
					11/05/1998
		11/04/2002			11/04/2002
		01/30/2007			06/26/2007
DJ Japan &	3	11/27/1996	DJ UK &	5	12/02/1996
DJI Japan		09/12/2003	DJI UK		07/09/1998
		11/26/2007			06/11/2002
					04/02/2003
					07/23/2007
DJ US &	4	03/26/1997	DJ World &	4	04/10/1997
DJI US		01/03/2000	DJI World		10/05/2000
		04/02/2003			05/19/2003
		10/30/2007			07/23/2007

Table 6: Measure of standard error in sub-samples and variance equality test

Sub-samples	Std. dev.	Sub-samples	Std. dev.	Brown-Forsythe's test
DJ Asia		DJI Asia		
01/01/1996 - 11/27/1996	0.63	01/01/1996 - 11/27/1996	0.65	0.71
11/28/1996 - 10/23/2002	1.29	11/28/1996 - 10/23/2002	1.41	0.00***
10/24/2002 - 07/26/2007	0.97	10/24/2002 - 07/26/2007	0.97	0.87
07/27/2007 - 12/31/2009	1.61	07/27/2007 - 12/31/2009	1.64	0.91
DJ Canada		DJI Canada		
01/01/1996 - 07/30/1998	0.79	01/01/1996 - 07/30/1998	0.93	0.00***
07/31/1998 - 04/23/2001	1.52	07/31/1998 - 04/23/2001	2.23	0.00***
04/24/2001 - 10/24/2007	0.96	04/24/2001 - 10/24/2007	1.29	0.00***
10/25/2002 - 12/31/2009	2.05	10/25/2002 - 12/31/2009	2.53	0.00***
DJ Emergent		DJI Emergent		
01/01/1996 - 01/16/1997	0.49	01/01/1996 - 06/13/1997	0.67	nc
01/17/1997 - 11/04/2002	1.12	06/15/1997 - 11/05/2002	1.76	nc
11/05/2002 - 01/30/2007	0.90	11/06/1998 - 11/04/2002	1.47	nc
01/31/2007 - 01/30/2007	1.72	11/05/2002 - 06/26/2006	1.02	nc
01/31/2007 - 12/31/2009	1.50	06/27/2006 - 12/31/2009	1.50	nc
DJ Japan		DJI Japan		
01/01/1996 - 11/27/1996	0.73	01/01/1996 - 11/27/1996	0.76	0.78
11/28/1996 - 09/11/2003	1.50	11/28/1996 - 09/11/2003	1.61	0.01***
09/12/2003 - 11/26/2007	1.19	09/12/2003 - 11/26/2007	1.16	0.51
11/27/2007 - 12/31/2009	1.83	11/27/2007 - 12/31/2009	1.82	0.68

The p-value is given for the Brown-Forsythe's test. "nc" means non-computed because the subsamples are not the same. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: Measure of standard error in sub-samples and variance equality test

Sub-samples	Std. dev.	Sub-samples	Std. dev.	Brown-Forsythe's test
DJ UK		DJI UK		
01/01/1996 - 12/02/1996	0.56	01/01/1996 - 12/02/1996	0.61	0.21
12/03/1996 - 07/09/1998	0.82	12/03/1996 - 07/09/1998	0.92	0.09*
07/10/1998 - 06/11/2002	1.16	07/10/1998 - 06/11/2002	1.32	0.00***
06/12/2002 - 04/02/2003	1.87	06/12/2002 - 04/02/2003	2.03	0.34
04/03/2003 - 07/23/2007	0.82	04/03/2003 - 07/23/2007	0.90	0.06*
07/24/2007 - 12/31/2009	1.86	07/24/2007 - 12/31/2009	1.90	0.56
DJI US		DJI US		
01/01/1996 - 03/26/1997	0.71	01/01/1996 - 03/26/1997	0.83	0.70
03/26/1997 - 01/03/2000	1.10	03/26/1997 - 01/03/2000	1.22	0.61
01/04/2000 - 04/02/2003	1.47	01/04/2000 - 04/02/2003	1.63	0.00***
04/03/2003 - 10/30/2007	0.81	04/03/2003 - 10/30/2007	0.78	0.18
10/31/2007 - 12/31/2009	1.83	10/31/2007 - 12/31/2009	1.81	0.46
DJ World		DJI World		
01/01/1996 - 04/10/1997	0.46	01/01/1996 - 04/10/1997	0.55	0.04**
04/11/1997 - 10/05/2000	0.89	04/11/1997 - 10/05/2000	1.01	0.00***
10/06/2000 - 05/19/2003	1.14	10/06/2000 - 05/19/2003	1.30	0.01***
05/20/2003 - 07/23/2007	0.60	05/20/2003 - 07/23/2007	0.63	0.16
07/24/2007 - 12/31/2009	1.36	07/24/2007 - 12/31/2009	1.38	0.82

The p-value is given for the Brown-Forsythe's test. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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